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The diffusion mechanisms of dynamic ridesharing services

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Abstract

A growing number of ridesharing apps is available to help users arrange real-time shared rides. Ridesharing service providers implement platforms that mediate between the requirements of drivers and riders to tackle the challenges of the chicken and egg problem: an intermediary should attract passengers by means of creating a large installed base of drivers who will be willing to register only if they expect that many passengers will adopt the service. Therefore, dynamic ridesharing services need to reach an initial critical mass of users in order to provide desirable level of matching between drivers and passengers.

To help in this task, the objective of this work is to investigate some of the levers that could boost the diffusion of a new ridesharing service. This is done by the means of a System Dynamics (SD) model. The model integrates existing diffusion models retrieved from the literature with the main outcomes of a project to which the authors contributed. Three main results are found out of simulation runs and case-scenario analyses. First, the service is expected to work effectively in densely populated urban areas, due to higher contact rates between users that turn in increased matching opportunities. Second,

since dynamic ridesharing has yet to be established as a valid alternative for private urban mobility, a high level of service is required. The combined effect of lower population density with high level of desired matching by users is substantially detrimental for the adoption of the service. Third, should the service provider decide to focus on just one type of user, it would have a negative long-term effect on the matching, leading to a higher discard rate of the service.

Keywords

System Dynamics; Technology diffusion; Ridesharing; Simulation

Introduction

Congestion-related problems are one of the most important issues cities around the world have to face, and a transition to alternative and more sustainable means of transportation is necessary to improve unsustainable mobility systems (Whitmarsh and Nykvist, 2008). A growing number of dynamic ridesharing apps that exploit smartphones and GPS-location based technologies is becoming available in many cities and countries to help drivers and passengers arrange real-time shared rides and broker any related information and payment services (Chan and Shaheen, 2012; Anderson, 2014).

Whatever their operating models or pricing mechanisms, ridesharing services operate as two-sided platforms to intermediate between the requirements of both communities of drivers and riders and to provide user-friendly and intuitive interfaces to encourage their adoption. As a matter of fact, ridesharing services are a relative new concept based on the sharing of personal trips between private users, in contrast with the traditional transportation industry that considers mainly the direct purchase of transportation services from professional drivers (e.g. taxi) or local public transportation companies. Therefore, dynamic ridesharing app providers face the same challenges as all other similar two-sided platforms, better summarized by the *chicken and egg* problem: “to attract buyers (*passengers*), an intermediary should have a large installed base of registered sellers (*drivers*), but these will be willing to register only if they expect many buyers (*passengers*) to show up” (Caillaud and Jullien, 2003).

Hence, dynamic ridesharing services need to reach a critical number of users, especially in the initial phase, in order to provide a desirable level of matching between drivers and passengers and overcome the chicken and egg problem. In particular, each failed match has more negative impact on passengers, who have to find alternative means of transport with little notice.

In this context, Lee and Savelsbergh (2015) investigated the effectiveness of using dedicated drivers as a way to overcome the issue of unmatched passengers. In particular, the authors observed that the higher the density of users, the lower the number of drivers, and the threshold beyond which drivers start decreasing is significantly lower wherever users are concentrated. As a matter of fact, ridesharing

services could implement different strategies of consolidating the demand in pick-up or meeting points in order to reduce the complexity of the coordination problem between drivers and riders (Furuhata et al., 2013; Stiglic et al., 2015). Consolidation of demand can also be achieved when selected group of individuals have the same destination, as in the case of employees of one company. This type of consolidation is beneficial to the process of matching users for two main reasons: first of all, participants share similar demographics and interests; and second, they make recurrent commuting trips (Naoum-Sawaya et al., 2015). In addition, more sophisticated matching algorithms can improve the performance of ridesharing services (Agatz et al., 2011) and longer detours in the launch phase may be instrumental for maximizing the matches and support the creation of a critical mass of users (Kleiner et al., 2011).

However, limited research is available to help identifying some of the key strategic factors that enable the adoption of a ridesharing technology, both internal and external to the ridesharing service, so that ridesharing service companies may be better assisted in assuming the right strategies to get both communities of clients on board. As a matter of fact, in the context of radical innovation, such as the case of dynamic ridesharing, forecasting the diffusion mechanism and identifying potential demand may support the decision making process of companies (Klasen and Neumann, 2011).

To help overcoming the literature gap and the associated strategic implications, the objective of this work is to explore and understand the levers that may facilitate the diffusion of a new ridesharing service, thus highlighting the most important success factors and providing some insights on the extent to which possible strategies could boost the service diffusion based on such success factors.

To this end, a System Dynamics (SD) model is developed by integrating existing diffusion models retrieved from the literature with the main findings of a case project to deliver a new ridesharing service.

The paper is structured as follows. Firstly, we explore relevant literature pertinent to the definition of ridesharing services, to the problem of new technology diffusion with particular focus on two-sided platforms, and to the usage of SD for the identification of trends and patterns of technology adoption.

Second, the project that funded the basis of our research is depicted, along with data collection performed to define different user needs and requirements. Then, the proposed SD model is explained together with the main results of simulations. A calibration phase is also provided in detail.

Finally, both practical and theoretical implications are proposed and conclusions drawn.

Literature Review

Ridesharing: definition and main characteristics

The idea of ridesharing was first introduced during World War II in the US, with the aim of saving resources for the war effort, but it has since then evolved and spread all over the world and nowadays automated ridesharing systems exploits a wide variety of enabling technology, such as GPS and smartphones, to provide more services like route-finding and instant notifications, delivered through web-based and mobile applications (Siddiqi and Buliung, 2013). Moreover, the adoption of these technology-based matching services is fostered through the increasing penetration of social networks, mostly because social networks are lowering some psychological barriers preventing ridesharing between strangers during the early years of the industry (Gargiulo et al. 2015). In fact, active users of social networks have greater risk taking attitudes (Fogel and Nehmad, 2009). Hence, they are more keen on sharing a ride with people they have never met.

Dynamic ridesharing has been defined as “a system that facilitates the ability of drivers and passengers to make one-time ride matches close to their departure time, with sufficient convenience and flexibility to be used on a daily basis”. Agatz et al. (2011) define dynamic ridesharing as “a system where an automated process employed by a ride-share provider matches up drivers and riders on very short notice, which can range from a few minutes to a few hours before departure time”. Levofsky and Greenberg (2001), states that “dynamic ridesharing systems consider each trip individually and are designed to accommodate trips to random points at random times by matching user trips regardless of the trip purpose”. The authors highlight some aspects that limit the adoption of dynamic ridesharing, such as the uncertainty of a return trip, safety concerns, and an overall lack of advertising effort. They also underline some important success factors for the diffusion of dynamic ridesharing services, such as Internet-based time-dependent dynamic matching systems and effective mechanisms to recruit the drivers. According to Furuhata et al. (2013), dynamic ridesharing “provides an automated process of ride-matching between drivers and passengers on very short notice or even en-route, specifying pick-up and drop-off locations and times based on the simple input of participants’ itineraries and schedules”. With this regard, the authors state that, depending on the type of ridesharing proposed by the matching agency, some issues may arise. For instance, if either pick-up or drop-off locations or both are not on the way of the driver’s route (detour ridesharing), drivers have to make real-time decisions on the convenience of the trip, since they incur in additional cost not paid by the passengers.

Summing up the definition retrieved in literature, dynamic ridesharing is characterized by the following features:

1. A third-party matching platform managing the interactions between the two users, drivers and passengers;
2. Ridesharing platforms make one-time ride matches, in the sense that matches are not repeated and take place at random points and at random times;
3. Ridesharing systems are flexible and can match users on very short notice;
4. The matching is proposed by accommodating users' trips, regardless of the trips' purposes

Services like Uber and Lyft match users on a short notice and make one-time ride matches, but in reality, they directly match drivers with passengers, without taking into consideration the trip accommodation of both sides. In this sense, they fulfil the first three features highlighted, lacking the last one, and therefore cannot be considered dynamic ridesharing by this definition.

The cost of ridesharing is a determinant factor for the adoption of this kind of services. For drivers for instance, the reimbursement fee should increase the convenience of sharing the ride as opposed to drive solo. This convenience could be achieved through both disincentives and monetary incentives for those who use ridesharing (Hwang and Giuliano, 1990). However, users have to make decisions based on a trade-off between the convenience given by the reimbursement fee and some of the inconveniences of dynamic ridesharing. The inconveniences might be related to losing privacy (Xu et al., 2015), having to coordinate with other users regarding the trip time and route (K. Arning, M. Ziefle, and H. Muehlhans, 2013) or having to combine the car ride with other means of transportation (Hansen et al. 2010).

Finally, Deakin et al. (2010) provided a synthetic and exhaustive background on the main features of dynamic ridesharing, as well as on the drawbacks and potentialities. The authors argue that dynamic ridesharing may require high cost of start-up and maintenance, covering marketing (e.g. incentives) and technical expenses (e.g. hardware and software).

The main success factors and drawbacks to the introduction of dynamic ridesharing are shown in Table 1.

Author	Success Factors	Drawbacks
Siddiqi and Buliung, 2013	Availability of enabling technology (GPS and Internet-enabled smartphones) Building relationships with organizations/employers, to whom provide customized solutions, (e.g. sharing rides with colleagues)	Cost inefficiencies Poor service levels Usability and technological limitations (e.g. interfaces) Security concerns
Agatz et al.	Availability of enabling technology (GPS and	Risk of not finding a return trip

(2011)	Internet-enabled smartphones) Fuel cost savings Positive word of mouth based on the success of matching algorithm Public incentives Offering service in high demand area	
Levofsky and Greenberg (2001)	Availability of enabling technology (GPS and Internet-enabled smartphones) Aggressive advertising Enhanced security measures Fuel cost savings Time savings	Poor service levels
Xu et al. (2015)	Availability of enabling technology (GPS and Internet-enabled smartphones) Fuel cost savings Time savings	Inconvenience related to loss of freedom and privacy Security concern
Arning et al. (2013)	Fuel cost savings	Lack of users' flexibility (i.e. willingness to coordinate with others and accept detours)
Hansen et al. (2010)	Availability of enabling technology (GPS and Internet-enabled smartphones)	Coordination and communication between users Psychological factors, such as scepticism about 'consume without ownership' Security concerns
Deakin et al. (2010)	Availability of enabling technology (GPS and Internet-enabled smartphones) Offering service in high demand area Flexibility of trip scheduling (i.e. users do not have to commit to a fixed trip) Fuel cost savings	Security concerns Risk of not finding a return trip Inconvenience related to loss of freedom and privacy

	Time savings	
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Table 1. Success factors and drawbacks of dynamic ride sharing services

Technology adoption models

There are several models available in the literature to explore the mechanisms of adoption of a new technology and the patterns of diffusion of a product or service by a community of users. Among them we find the Gompertz model (Gutiérrez et al., 2005), the logistic model (Richardson, 1991), the Fisher-Pry model (Fisher and Pry, 1971), and the Bass diffusion model (Bass, 1969).

In particular, the Bass diffusion model is used as a foundation for this work. The Bass diffusion model assumes that the growth of adopters of a new product or service is triggered by word of mouth between adopters and potential adopters. Word of mouth increases over time as the installed base of adopters increases. The Bass model overcomes the shortcomings of other models in depicting the S-shaped curve line of adoption for a new technology or innovation. Such barrier can be underlined in the fact that other models consider zero as an equilibrium, while for a diffusion process some initial population is necessary for the adoption from word-of-mouth to start. Therefore, diffusion is initiated through external sources of information whose effects are roughly constant over time and are best expressed by the effect of advertising, which causes a constant fraction of potential adopters to adopt the service.

The Bass model has been applied to a variety of sectors, such as ICT, retail, agriculture, pharmaceuticals, and industrial goods. It has been deemed to be at the same time intuitive and showing high potential for predicting behaviour of a system (Daim e Suntharasaj, 2009).

Two-sided platforms

While diffusion models typically involve the analysis of just one community of consumers adopting a technology, for the study of the diffusion dynamics of a ridesharing service the interactions between drivers and riders must be considered in addition to the diffusion of the service among the users of each separate community. In fact, the value of two-sided platforms is dependent on the participation of users at both sides, since we can assume that the value for one side of participating in the platform increases with participation from the other side. This process is catalysed through the network externalities that develop between users, both inter-side externalities between the two groups and intra-side within the same side community. Roson (2005) highlights two sources of inter-side externalities: *single interaction externality* exists when one type of matching is realized between the two sides, and the quality of the matching improves with the possible alternatives. On the contrary, when more interactions are made possible by the presence of more partners (e.g. having access to different goods if more suppliers are available) the platform gains value from *multiple interaction externality*. The author

argues that in case of single interaction externalities the numbers of agents in the opposite side may cause decreasing return on utility, as opposed to the multiple interaction case where returns could be constant.

Modelling the technology diffusion problem with SD

SD has proved itself to be an appropriate approach to help studying the process of innovation and technology adoption by communities of users and customers. Based on system thinking theory, SD is a modeling and simulation environment that assists in solving complex problems via representing a system as interconnected cause and effect variables in multiple reinforcing and balancing feedback loops (Sterman, 2000). SD has been used to understand complex problems in various industries and applications and, in particular, to capture the archetypical “growth and plateau” behaviors that characterise the S-curve line of technology adoption by a community of potential adopters. To this end, several works are available in the literature, such as the ones by Maier (1998), Milling (2002) and Tsai and Hung (2014). Most of these works share a common foundation in the original Bass technology diffusion model, which considers the rate of adoption as summation of two adoption rates, namely from word of mouth and from advertising, as per Equation 1 and Equation 2.

$$\text{Adoption rate from advertising} = aP \quad (1)$$

$$\text{Adoption rate from word of mouth} = ciPA/N \quad (2)$$

Where P is the population of Potential adopters, A the population of Adopters, a the advertising effectiveness (adoption fraction from advertising), c the contact rate between individuals in a population, measured in people contacted per person per time period, i the adoption fraction from word of mouth, and N the total population.

Potential adopters generate as much as cP contacts for each time period. Potential adopter interact with adopters and the probability that each potential adopter has to get in contact with an adopter is the fraction of total adopters A/N . Therefore, the total amount of interactions between adopters and potential adopters for each time period is cPA/N . However, only a portion i of these interactions turns out as a successful adoption.

The theoretical background for the model proposed in this paper is also provided by some modified and refined application of the Bass model by Thun et al. (2000) who develop a SD model to understand the diffusion process of goods with network externalities. The utility of products with network externalities is a function of the installed base B_t , referred to as the cumulated amount of users at time t . The Utility is expressed through a dimensionless variable, namely: the average utility per user. This variable is a function of the number of interconnections (i.e. number of users divided by two) and a parameter that

determines the number of interconnections that are valuable to the user (i.e. relevant adopter fraction). Compared to the Bass model, the one by Thun et al. (2000) considers the adoption fraction as influenced by the average utility per user. In the first step of their process, the authors make a simple assumption that the two variables are equal. Then, they relax this assumption by including a parameter, the desired utility, which is used in comparison with the average utility. If average utility is higher than desired utility, all users adopt the product. Otherwise, only a portion of users adopts it. This portion depends on the gap between actual and desired utility (i.e. ratio average utility/desired utility) and on the risk individuals are willing to take for acting as first adopters. The same rationale is applied to the discontinuation fraction and discontinuation rate, which respectively represent the portion and the total amount of users that quit if the product fails their expectations. The discontinuation fraction is the complementary to one of the adoption fraction; the discontinuation rate is the discontinuation fraction multiplied by the installed base and smoothed over time by a parameter, named as “patience” that expresses the period of time users are willing to wait before discarding the product.

Case Project and Research Methodology

A SD model is developed to support a research project to design and test a dynamic ridesharing mobile platform capable of providing the best real-time matching for the two participating sides (drivers and riders) based on a trust metrics and preselected constraints, such as a maximum detour allowed from the original planned route for picking up a passenger.

One of the primary objectives of the research project is to understand the levers that might facilitate fast and lasting adoption growth by both populations of drivers and riders via the formulation of a service diffusion SD-based model for ex-ante simulation of the potential successfulness of the proposed ridesharing service.

For this purpose several tasks have been carried out.

First, some main SD-based technology diffusion models available in the literature are studied. Then, data are collected through focus groups and an online survey. Second, the model is developed by integrating and modifying the two main foundation models, namely the Bass model and the one by Thun et al. (2000). Third, we calibrated the model by estimating the values of the parameters, according to the focus groups, the questionnaire and findings from the literature. Finally, we performed simulation runs over a time frame of 200 weeks. We used Vensim DSS by Ventana Systems for the simulation runs.

Data collection

Two focus group sessions and one questionnaire are used as tools to gain knowledge on users' requirements and behaviours to model the intra and interconnections between the users of the communities.

- Focus groups

From 7 to 9 persons participate to each focus group and they are requested to both evaluate the service concept from their specific perspective and improve it by either adding or cutting functionalities. At the end of both sessions, the main user requirements and specifications are defined.

- Questionnaire

The questionnaire is developed to understand the market potential of this service by means of asking users their predisposition to sharing car rides, their mobility habits, and their opinion on the features of the service, such as the fee and the maximum acceptable waiting time.

Model development

As previously mentioned, we developed the model via an integration and adaption of two foundation models. On the one hand, based on the concept that this service is a two-sided platform, the system is divided into two different populations of Drivers and Passengers, each one with separate, although similar, feedbacks and dynamics.

On the other hand, the model provided by Thun et al. (2000) is modified according to some specific features of the ridesharing platform at issue, such as the existence of a reimbursement fee that passengers must reimburse to drivers.

Calibration of the model

The values of the parameters of the model are estimated through the usage of the mentioned focus group interviews, the administered online survey and previous literature. For instance, the sensitivity to the reimbursement fee of both drivers and passengers is calculated with the percentage of users that would adopt the service for different levels of the fee. Moreover, the parameter Patience is a proxy of the number of failed attempts to ridesharing that a driver or a passenger is willing to stand for.

The effectiveness of the service is measured with the quality of the matching proposed. To this aim, the findings from Agatz et al. (2011) related to the success rate as a function of the penetration rate of the service are integrated as parameters of the simulation. Agatz et al. (2011) provided a simulation on the

metropolitan area of Atlanta, a sprawling region that can resemble most of the main metropolitan areas in the world.

The ridesharing service diffusion model

The complete model is given in Figure 1. The most important variables and feedback loops are explained in the next sections, while the full list of equations is given as a Supplemental Material.

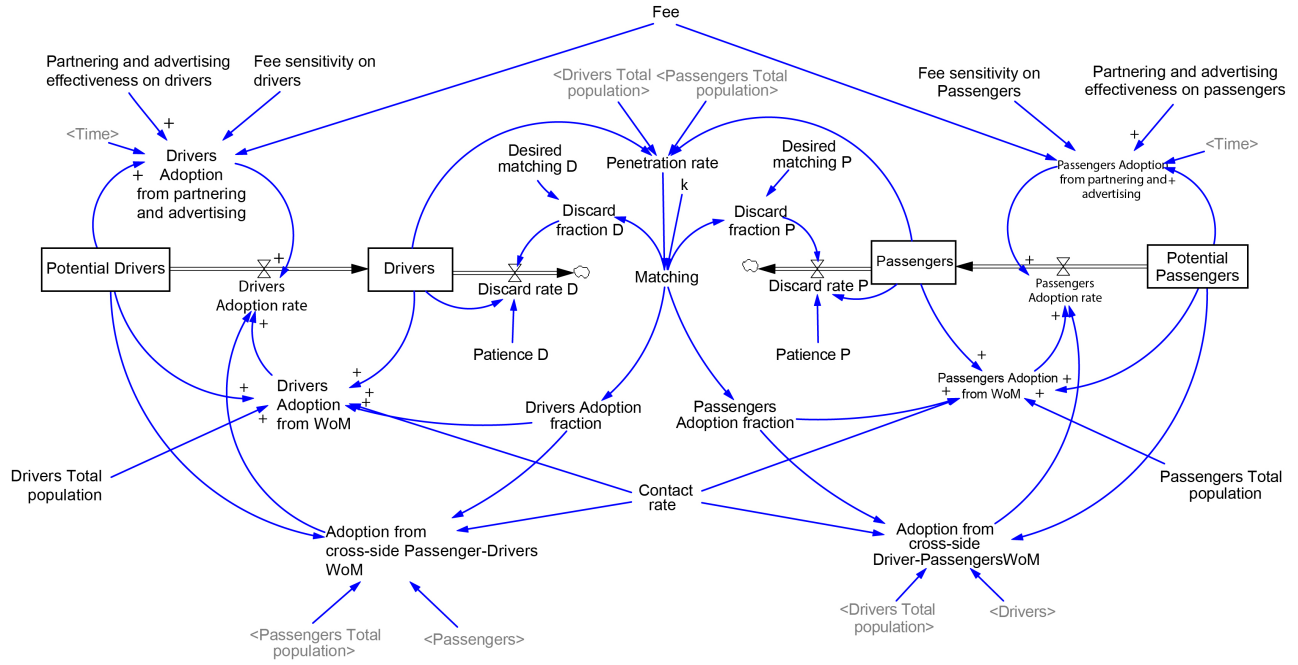


Figure 1 Ridesharing adoption model

Adoption rate from advertising and partnering

Two factors can trigger the growth of the population from external sources. The first factor is represented by the advertising and partnering effectiveness, while the second one is the value of the fee that is reimbursed to the driver. Both populations adopt the service as a result of the effect of the advertising and the partnering actions, such as discounted car insurance premiums for drivers or free/discounted tickets for museums and other amenities for riders. The rate at which the two populations adopt the service as an effect of partnering depends on the maturity of the service in the market. Therefore, we introduce an initial start-up period during which the app increases its partner's base, leading to the full potential of partnering effectiveness after 100 weeks (2 years).

As far as the second factor is concerned, it can be noted that the service fee has an opposite effect on the two populations, since its increase will incentive Drivers to enter the service and Passengers not to adopt it, and vice versa. The adoption rate is not directly related to the value of the fee, but is mediated by another variable, named as "Fee sensitivity", which shows how many Passengers and Drivers are

adopting if the service fee is increased or decreased. The parameter Fee sensitivity is a lookup table, that was retrieved from the results of the survey to the users. The values of the parameter Fee are retrieved from a specific question of the survey, asking which is the most appropriate reimbursement for drivers for a 10 km long trip. Users could choose between 1.5 € (0.15 €/km) and more than 5 € (we assumed 0.6 €/km). In the SD model, the amount of potential users for each level of the fee is equal to the cumulative percentage of users who gave their preference up to the correspondent level. Fee sensitivity is opposite for the two populations, since the highest rate of adoption for drivers takes place with the highest fee, and vice versa for passengers.

The adoption rate for Drivers and Passengers is shown in Equation 3 and 4.

Drivers AR from partnering and advertising = Potential Drivers * (Fee sensitivity on drivers(Fee)) * (Partnering and advertising effectiveness on drivers*Time/100) Equation 3.

Passengers AR from partnering and advertising = Potential Passengers * (Fee sensitivity on Passengers(Fee)) * (Partnering and advertising effectiveness on passengers*Time/100) Equation 4.

Adoption rate from WoM

Word of mouth (WoM) plays a very important role in the diffusion of this kind of services, especially in a period where social media are thriving and multiplying the probability of contacts between users (Kietzmann and Canhoto, 2013). WoM is strictly related to the effectiveness of the service itself, represented by the probability that any user has to receive or give a ride. To model the effectiveness of the service we introduce the variable Matching (Equation 5), as a function of the penetration rate of the service, following the findings from Agatz et al. (2011). The variable “Matching” does not relate to the actual quality of the matching algorithm, which is considered as a given feature of the service.

Matching=k(Penetration rate) Equation 5

It has to be noted that the correlation between Matching and Penetration rate is non-linear, meaning that the highest increase in the effectiveness of the matching takes place in the first. The non-linearity was constructed by means of interpolating the findings by Agatz et al. (2011), using their three combination of participation rate-matching success, and adding a fourth one by setting a 100% matching success with the 100% participation rate. The result is logarithmic correlation between success of matching and participation (penetration) rate (Equation 6), with a $R^2 = 0.99068$:

Success of matching = $\ln(\text{Participation rate}) * 0.0878 + 1.0071$ Equation 6

From the derivative of this equation, it is clear that there is a much higher improvement of the matching at the beginning of the growth curve, when participation rate is still considerably low. To account for

this in the lookup table, and therefore to avoid major errors in the calculation of the matching success, we inserted more points when participation rate lies below 1%. Figure 2 shows the lookup table with the non linear correlation.

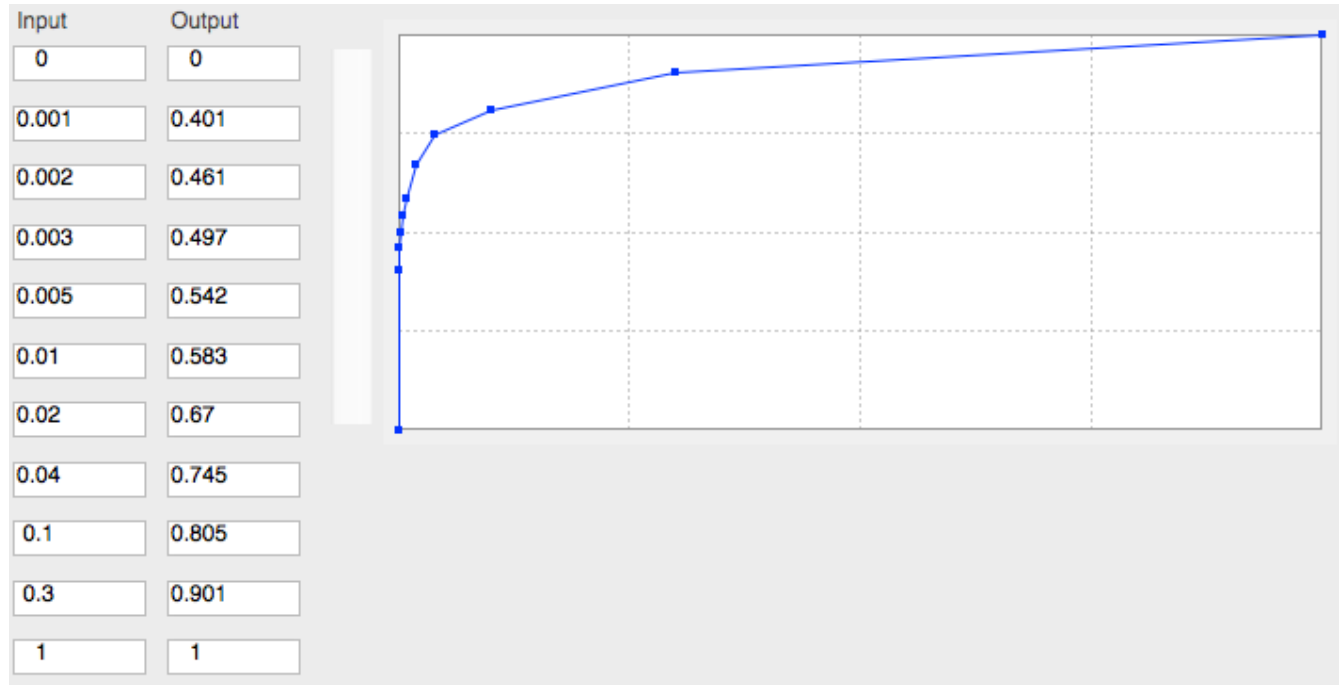


Figure 2 Look up table Penetration rate-Matching

In the original model, the adoption fraction is seen as a constant variable; in our model instead this is dependent on the effectiveness of the service, therefore it is set as equal to “Matching”.

Same-side and cross-side WoM

Adoption from word-of-mouth spreads over two kinds of effects that are considered in the model: the same side effects Drivers-Drivers and Passengers-Passengers, and the cross-side effects Drivers-Passengers and Passengers-Drivers. In other words, Passengers will adopt as a result of word of mouth from both their peers (other Passengers) and members of the other population group (Drivers).

The same-side adoption from word of mouth is established as in the original Bass model. The cross-side adoption from word of mouth is as per Equations 7 and 8.

$$\text{Adoption from cross-side D-P} = \frac{\text{Contact rate} * \text{Passengers} * \text{Adoption fraction} * \text{Potential Passengers} * \text{Drivers}}{\text{Drivers Total population}} \quad \text{Equation 7}$$

$$\text{Adoption from cross-side P-D} = \frac{\text{Contact rate} * \text{Drivers} * \text{Adoption fraction} * \text{Potential Drivers} * \text{Passengers}}{\text{Passengers Total population}} \quad \text{Equation 8}$$

Discard rate

The effectiveness of the service is not only related to the adoption fraction, but also to the Discard Fraction, its direct opposite. In fact, in the same way that users adopt if the matching works, they will disinstall the app or quit the service if it does not. Taking from the model of Thun et al. (2000), every two-sided platform has to generate a utility for both group of users so that users would stay in the platform if their desired utility is matched by the service. The discard fraction is therefore directly proportional to the ratio of the perceived utility experienced by the user and its desired utility. In our model the utility is given by the effectiveness of the service expressed through the variable “Matching”, as per Equation 9.

$$\text{IF THEN ELSE}(\text{Matching} \geq \text{Desired matching}, 0, 1 - \text{Matching} / \text{Desired matching}) \quad \text{Equation 9}$$

The discard rate DR is smoothed over a “Patience” parameter which expresses the time that users are willing to wait for the service efficiency to improve, as per Equation 10.

$$\text{Discard fraction} * \text{Adopters} / \text{Patience} \quad \text{Equation 10}$$

The same equations are used to express the discard fraction and the discard rate for both population groups (i.e. Drivers discard rate is equal to $\text{Discard Fraction Drivers} * \text{Drivers} / \text{Patience Drivers}$) but with different parameters. In fact, Passengers are likely to be more exposed to the consequences of a failed matching because they have less options of transportation and are more risk averse. Hence the two parameters, namely Desired Matching and Patience, are set at higher values for riders than for drivers.

Scenario simulations and analyses

The parameters of the model, their range of values and the base case values are shown in Table 2.

Parameter	Range	Base case
Fee	0.15-0.6 €	0.35 €
Partnering and advertising effectiveness on drivers	0-0.005	0.001
Partnering and advertising effectiveness on passengers	0-0.005	0.001
Desired Matching P	0.01-1	0.8
Desired Matching D	0.01-1	0.7
Patience P	0-26 weeks	2
Patience D	0-26 weeks	4

Table 1 Parameters of the model

Simulations start from an initial population of 30 Drivers and 10 Passengers.

The base case simulation shows that market saturation is not reached within the simulation time frame, and that Drivers grow at a faster pace. Both populations reach the tipping point soon after the discard rate starts decreasing, as the adoption rate follows a linear growth (Figure 3 and 4). Discard rate decreases as soon as matching success reaches the level of matching required by the user (i.e. Desired matching).

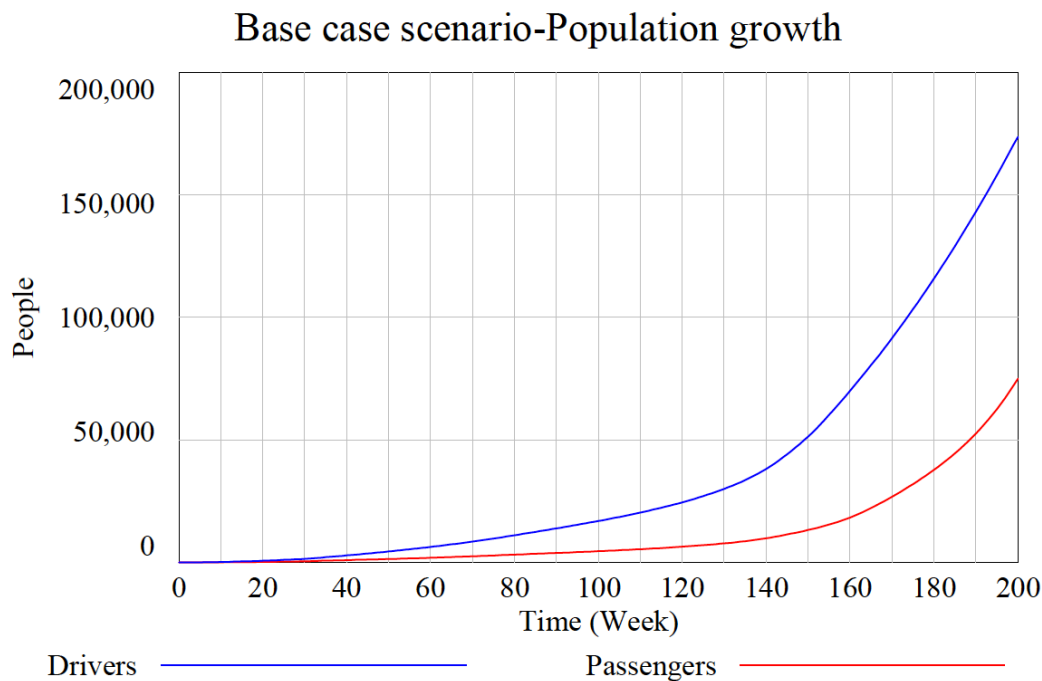


Figure 3 Population growth for the base case scenario

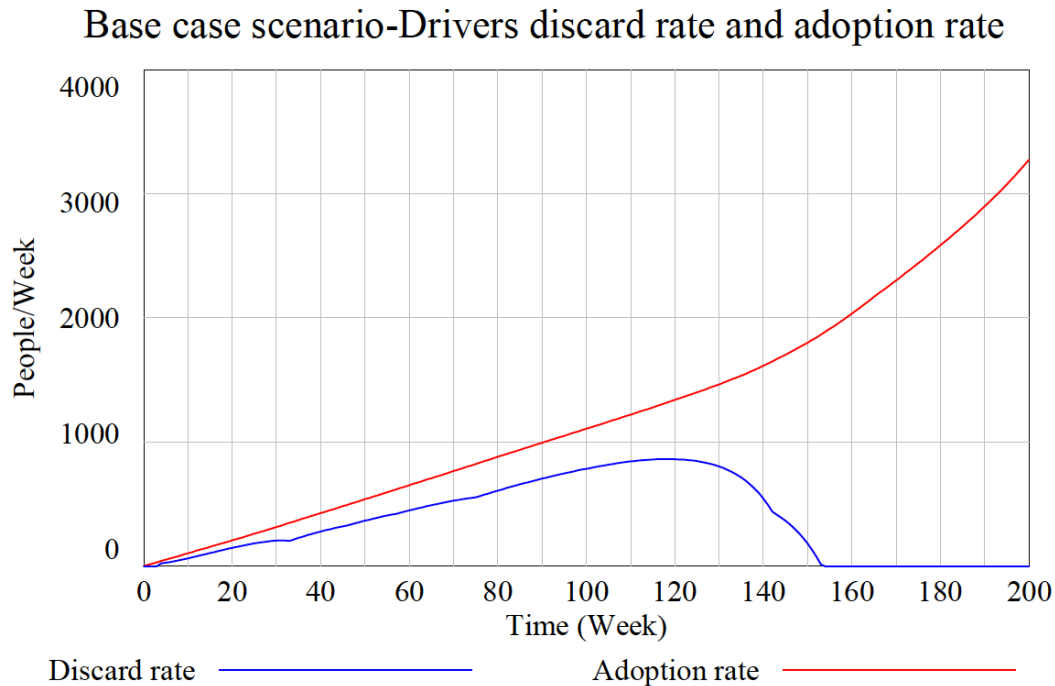


Figure 4 Drivers discard and adoption rate for base case scenario

For the base case scenario, it is necessary to reach a 10% penetration rate to reach the level required by both population (passengers require a higher level of matching).

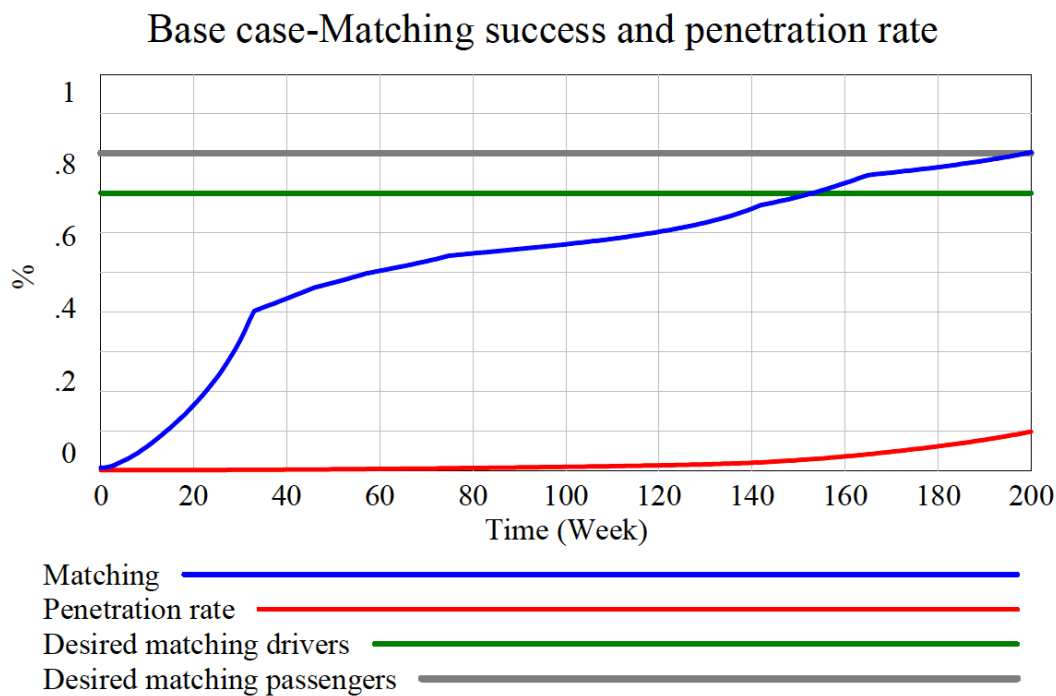


Figure 5 Different penetration rate required to achieve the desired matching for the base case scenario

The manipulation of the external factors has a direct effect on the time it takes for the service to reach the tipping point or, in other words, the point in time when the positive loop dominate the negative ones and the innovation spreads very quickly.

Figure 6 and 7 compare the S-shaped curve line growths of the communities of Drivers and Passengers for different parameter settings.

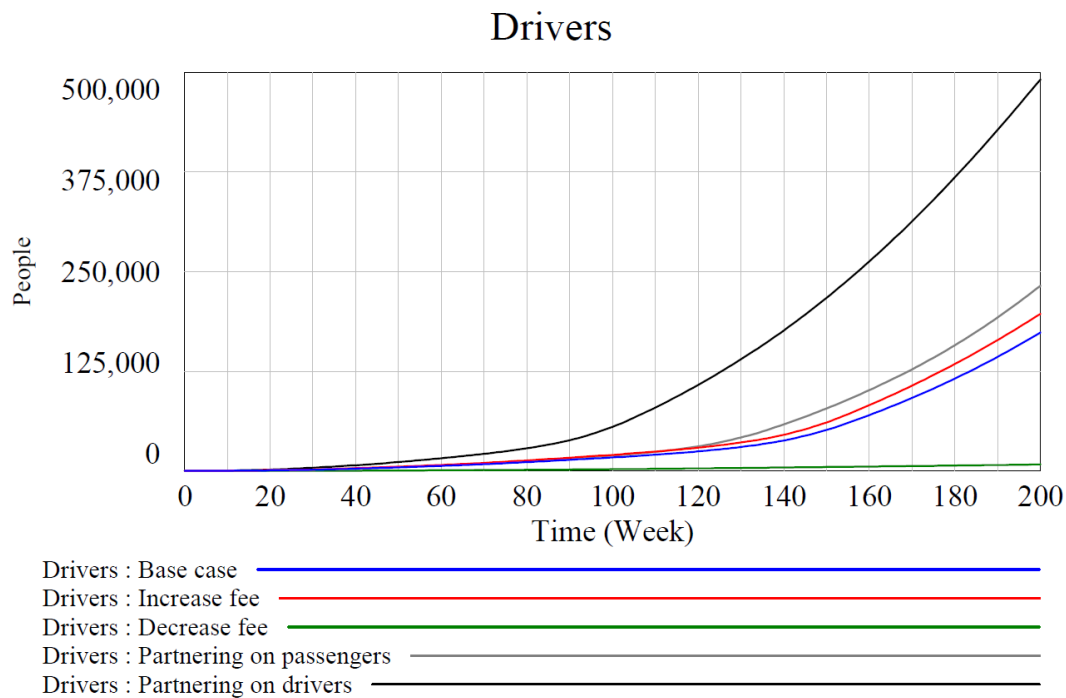


Figure 6 Drivers community growth with different external parameters settings

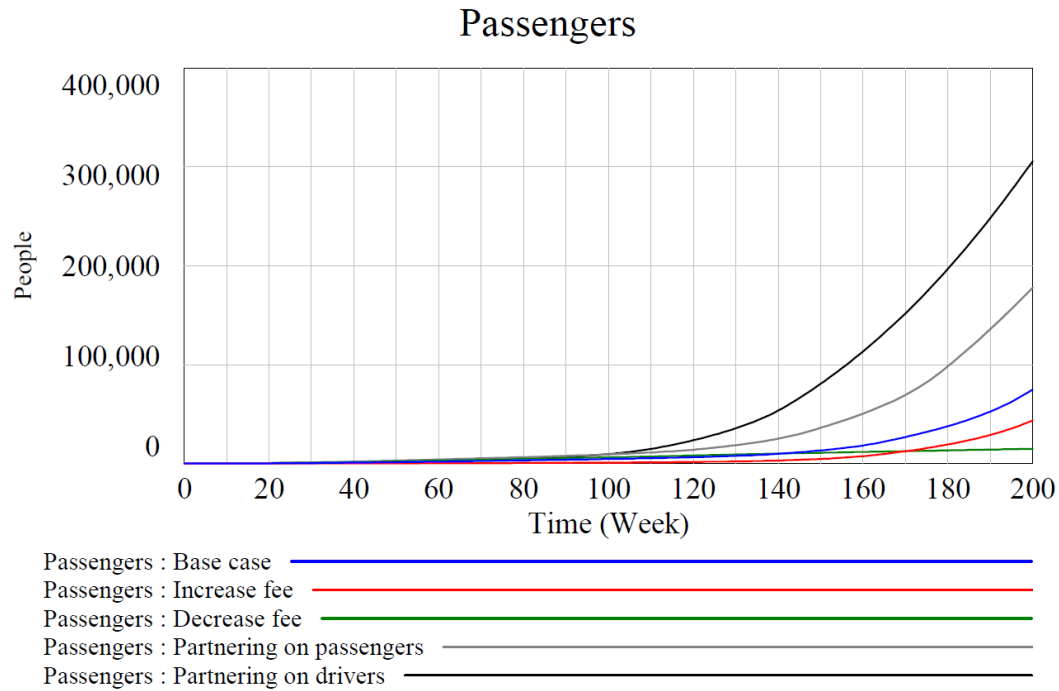


Figure 7 Passengers community growth with different external parameters settings

An increased partnering effectiveness, either on drivers or passengers, has a substantial positive effect on both populations' growth, because it enables to build critical mass more quickly on one population without negative effects on the other. As seen in the graphs, the effect of the partnering action is greater than the effect induced by any increase or decrease in the service fee. As far as the fee of the service is concerned, not surprisingly we found that setting the service fee at the maximum level, shown in simulation run "Increase fee", would generate more adoption from drivers and less adoption from passengers. However, when setting the fee at the minimum level (simulation run "Decrease fee") both communities do not grow and thus the adoption curve never reaches the tipping point. This apparently counterintuitive result can be explained in light of the gap in the required effectiveness of the service by the two populations, as Passengers have a higher desired matching and therefore usually higher discard rate during the first weeks of adoption, when the matching proposed does not meet the desired matching. Hence, if the ridesharing company should intend to attract more passengers by offering a lower service fee, it would potentially cause a higher overall discard rate (compared to the base case) with negative outcomes on the penetration rate, which is the independent variable for improving the level of matching proposed. As a consequence, even more passengers could abandon the service and the reinforcing loop created by the adoption from word-of-mouth could cease to take place.

In order to further assess what factors could affect the failure or success of the service, we also have to take a look at the endogenous variables responsible for the adoption from Word of Mouth. In this case, the levers of control are the following:

- *Patience* and *Desired Matching* represent the level of service required by the user. In other words, this is the utility perceived that affects both the discard rate and the adoption fraction;
- *Contact rate* increases the contact between adopters and non adopters and will result presumably in more adoption from word of mouth.

Univariate and multivariate analyses re illustrated in the next sections.

Patience and Desired Matching

Figure 8 shows the adoption growth associated to different settings in the desired matching, assuming the same increase or decrease for both population, finding significant effects on the matching level, both positive and negative. Further simulations have been performed in order to account for the possibility that drivers are more demanding than passengers regarding the effectiveness of the matching service, an assumption opposite to the one made during the development of the model. In this case, the adoption curve would still achieve a tipping point, but with less adopters. This could be a direct consequence of the service fee: the fee sensitivity assigned to the level used for this simulation corresponds to more drivers than passengers keen on adopting the service.

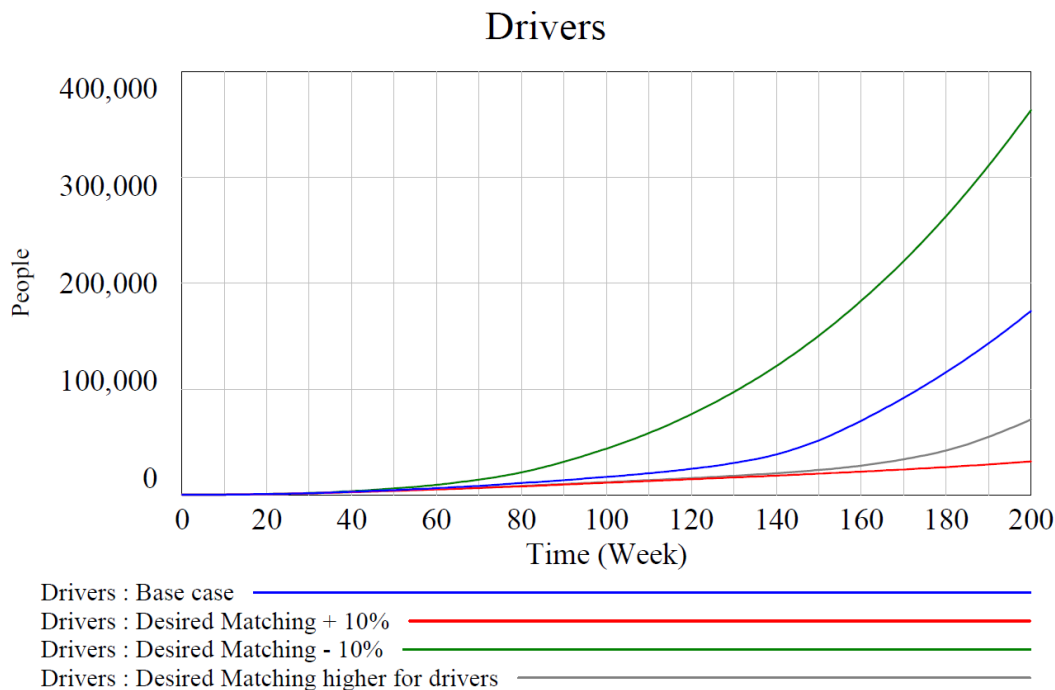


Figure 8 Effect of desired matching on drivers' adoption

The parameter Patience has a similar influence on the outcome of the simulations. Figure 9 shows the results for passengers' adoption with different parameter settings. In particular, simulation runs named "longer patience" and "shorter patience" depicts what happens when patience is respectively doubled and split in half for both populations; two further simulations are run to test whether longer patience on only one population may have different outcomes. As a matter of fact, it appears that positive consequences for passengers take place if drivers are more patient.

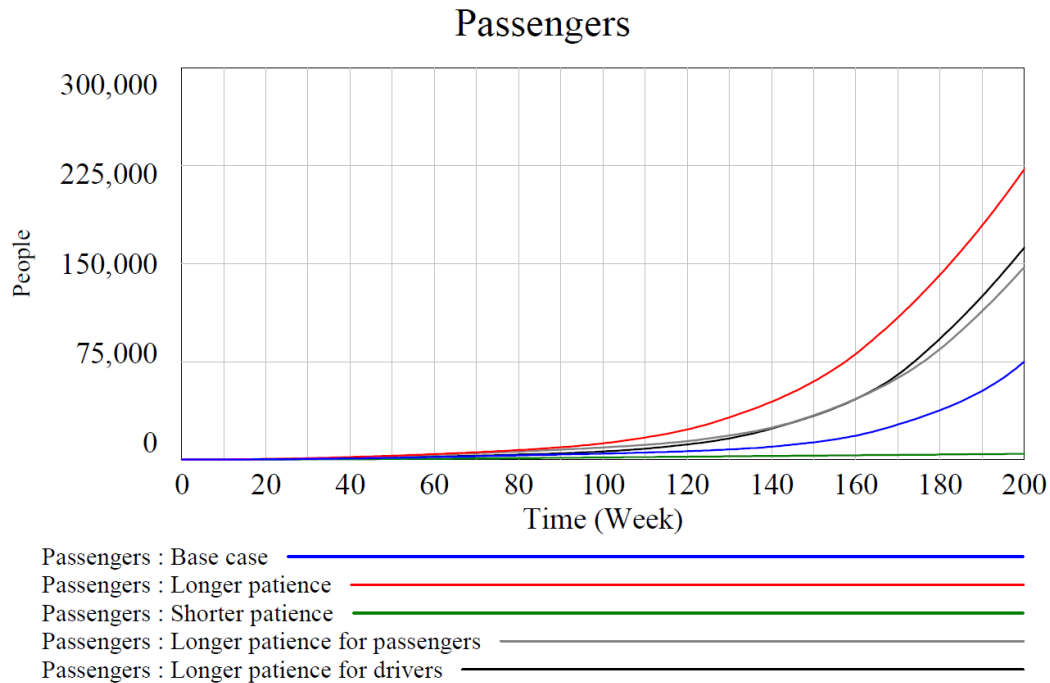


Figure 9 Passengers' adoption for different Patience settings

Figure 10 shows a comparison between the different influences of the two parameters. By comparing the two parameters, it can be noted on the one hand that a lower desired matching supports the population growth more than a longer patience. On the other hand, a higher desired matching jeopardizes the growth less than a shorter patience.

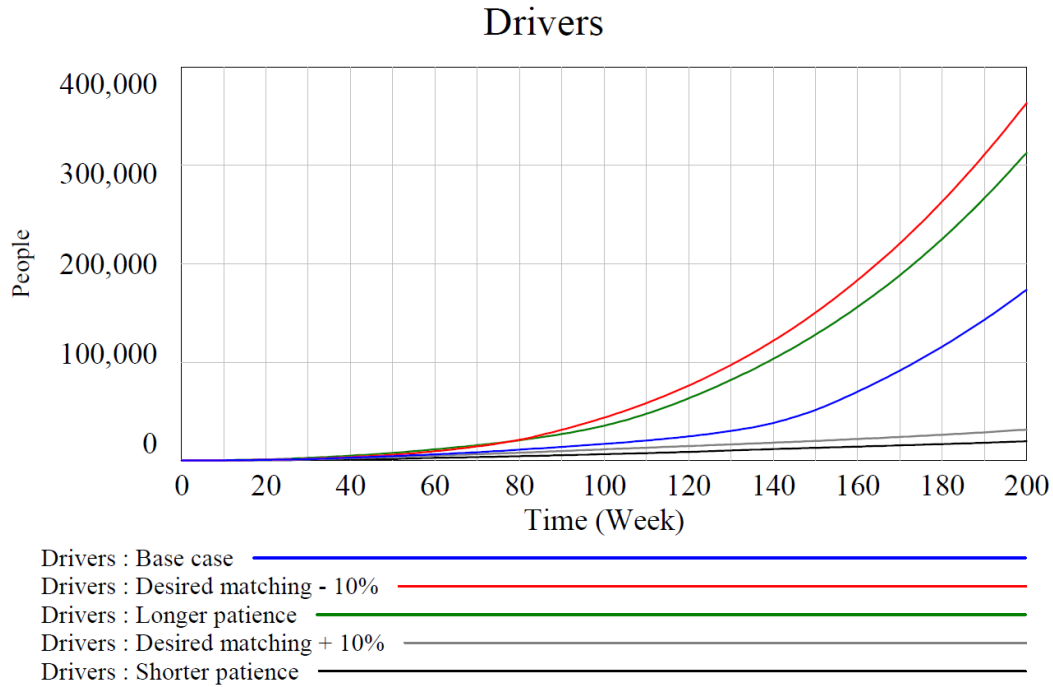


Figure 10 Effects of both patience and Desired Matching on Drivers' adoption

In order to further test the relative importance of the two parameters, we performed simulation runs by modifying the two parameters with the opposite sign, as seen in Figure 11. For instance, we increased Desired matching by 10% while extending the Patience, and vice versa.

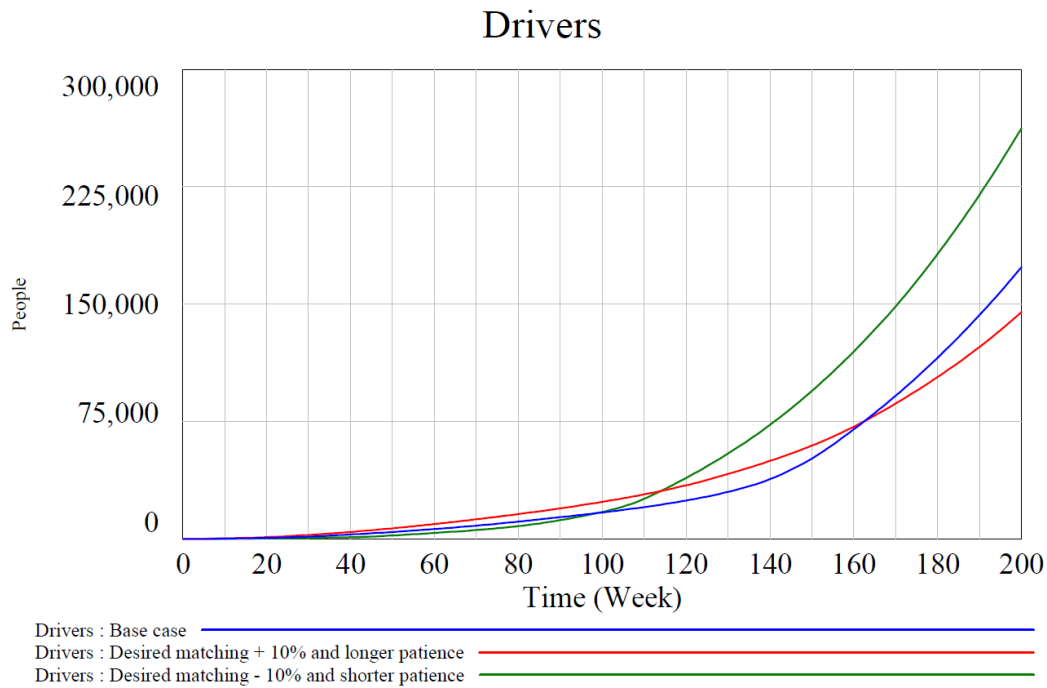


Figure 11 Drivers' adoption, Desired matching and Patience

From these simulations results it can be then assumed that a lower desired matching is more beneficial to the success of the service than a longer patience. As we can see from simulation run “Desired matching + 10% and longer patience”, when users are willing to wait longer time for an effective service, the adoption curve is higher than in the base case scenario, since less users will abandon the service from the beginning. However, a higher desired matching directly reflects on the period in time when the matching proposed finally reaches the desired level and users cease to leave the service. Graphically, this fact is represented by the adoption curve beginning to grow more steeply (i.e. reaches the tipping point). Figure 12 depicts this situation.

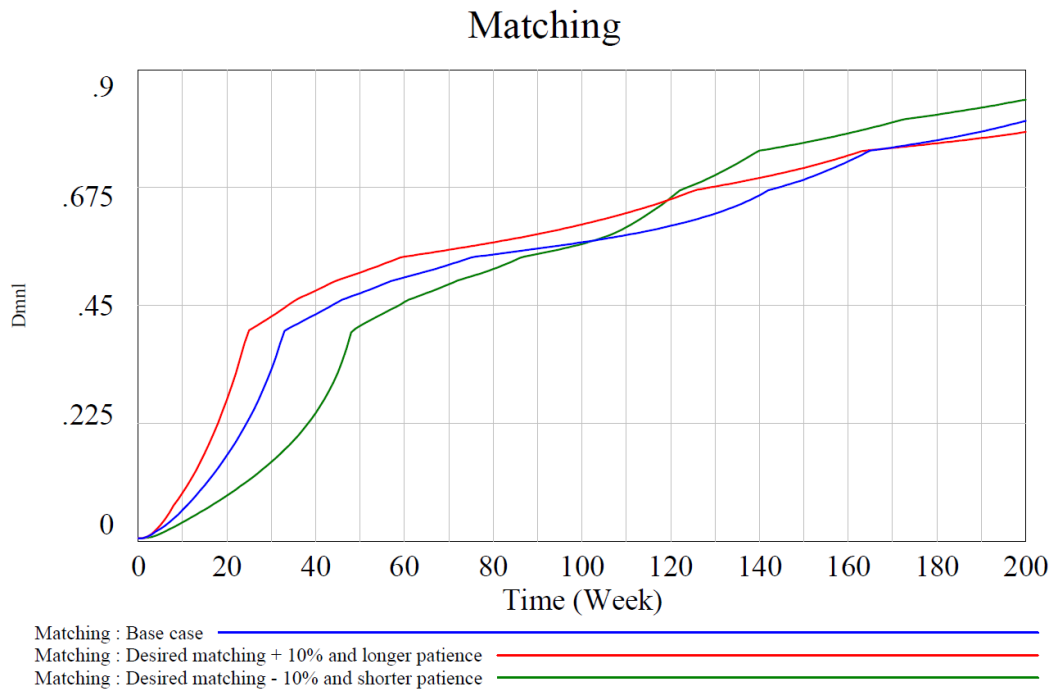


Figure 12 Effect on Matching of different combination of Desired matching and Patience

Also, the simulation run “Desired matching -10% and shorter patience” generates an interesting argument. In fact, this combination of the two parameters has a negative impact in the first weeks of simulation period on the matching provided by the service. As a matter of fact, the matching in this case remains lower compared to the other simulations shown in Figure 12 until week 103, when it equals the Base case scenario Matching, and week 120, when it finally overcomes the Matching from simulation “Desired matching + 10% and longer patience”. We can explain this occurrence by considering that a shorter patience leads to higher overall withdrawal rate from the service within the first weeks, when the proposed effectiveness of the service is not able to match the desired one. On the

other hand however, a lower fraction of adopters abandons the service if the desired matching is low enough, with positive effect on the speed to which the matching proposed improves during time. Nevertheless, the results of the combined simulations Desired matching-Patience are heavily influenced by the relative changes made to the parameters in the simulation runs.

Contact rate

The simulation shows that an increase in the Contact rate largely improves the Adoption from WoM and the total population growth rate in the first weeks, and the system reaches the total population of adopters with a contact rate of 0.05. In Figure 13 the effects on drivers adoption from WoM and total adoption are shown.

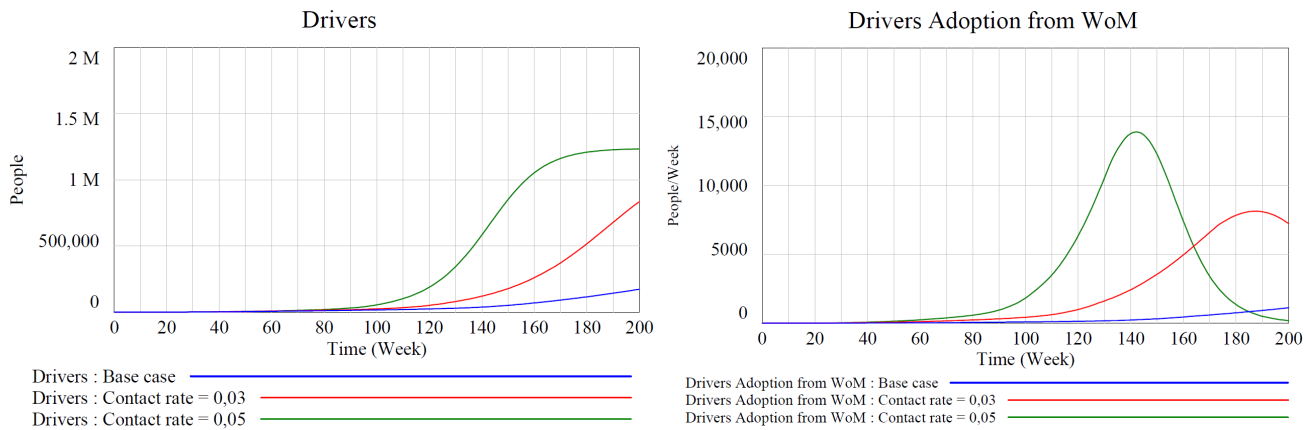


Figure 13 Effects of contact rate on Drivers adoption from WoM and total adoption

Discussion of results

The presented simulation runs and case scenarios analysis suggest three main considerations with regard to the most important levers that are likely to boost and control a successful diffusion of a dynamic ride sharing service.

First, the service is expected to work effectively in urban areas that are densely populated, such as city centres and congested urban environments. This is likely due to higher Contact rate and increased Matching because drivers are able to frequently reach their riders and quickly serve their urban trip destinations.

Second, the Desired matching represents the minimum service requirement. If this is not met, users would quit the service. Since dynamic ridesharing has yet to be established as a valid alternative for private urban mobility, it is assumed that users are less willing to “forgive” any failures in the service, and, therefore, the base case takes into account a high level for this parameter. The effect of a high level of desired matching is substantially detrimental for the adoption of the service. This evidence

suggests the need for an efficient backup service that would replace a failed matching between private drivers and passengers, such as a discounted taxi service.

Third, the parameter Patience appears to have similar influence on Drivers and Passengers' adoption, with obvious positive effect if users are more willing to wait for the matching to reach the desired level of service. Furthermore, this parameter needs to be taken into account in combination with the Desired matching. In fact, under certain circumstances, we showed that Patience could represent an even stronger barrier for the diffusion of a ridesharing service.

Fourth, the two populations can grow at a different pace under certain circumstances, and it is possible to enhance the adoption of the service by focusing on one population only. In particular, drivers are more important to the service, and hence it appears that increasing the fee of the service to please the drivers is beneficial to the service. Moreover, a more effective partnering action on drivers leads to more adoption by passengers as well. However, the analysis shows that if the service provider would decide to focus only on the Passengers' side by means of decreasing the fee, it would generate a negative effect on the matching, leading to a higher discard rate.

This work and associated lessons learnt originate both theoretical and practical implications.

From a research perspective, this is a contribution to the exploration of the applicability of SD to the domain of two-sided platforms (Rochet and Tirole, 2003; Armstrong, 2006). In fact, the proposed SD model proves itself a valid methodology to study the complex relationships between the interactive communities of two-sided digital services.

For managers and practitioners of two-sided digital services, this work can assist in the definition of the service design and value proposition and in the identification of the main levers of control for a more consistent business model. This is better elucidated while looking for instance at the combined and opposite effect generated by Patience and Desired matching, requiring the ridesharing platform management to accurately survey users to understand their requirements in terms of desired level of service and willingness to wait for "better times".

Moreover, ridesharing companies need to monitor continuously the actual effectiveness of the service against the predicted one. In fact, as shown by some scenario simulation, a low matching by the service in the first weeks does not necessarily translate into long-term failure of the service. Therefore, ridesharing companies need also to check for the tipping point of the adoption curve and the relative improvement of the matching rather than its absolute values.

Conclusion

This work investigates diffusion of a ridesharing service as a two-sided platform where two types of users, namely drivers and passengers, get together to enhance the effectiveness of the service itself, triggering network externalities. This problem has been tackled by means of a SD model, a methodology that has proven its effectiveness for capturing the mechanisms of diffusion of innovations and new products. The model integrates a refined version of the Bass diffusion model with a new SD model elaborated for understanding the diffusion of products with network externalities, and it is divided into two different populations of Drivers and Passengers, each one with separate, although similar, feedbacks and dynamics.

The values of the input parameters have been retrieved from focus groups and a survey administered to a panel of users.

Results show that without the initial boost to the population growth provided by advertising, the service can not prove to be successful. The externalities that take place between the two sides are expressed by the variable Matching, which is substantially affected by the penetration rate of the service, calculated as the sum of Drivers and Passengers communities. Based on the assumption that users require a high level of desired matching, to increase the penetration rate the ridesharing platform should offer the service only in urban areas showing a high concentration of users and hence a high contact rate. Moreover, it should focus on the partnering and advertising action, especially toward the population of Drivers. In addition to the high level of desired matching, an even stronger potential barrier to the success of the service could be related to the short patience expressed by users that do not want to wait for a more effective service. The most effective way to reduce these barrier is to propose a backup service that is offered to users when the platform is not able to find a proper matching.

Future research will be directed towards further validation of the parameters, and the refinement of the model, including new variables representing other facets of the problem such as the backup service or alternative modes of transport.

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